A Hybrid IoT and Deep Learning Approach for Real-Time Vehicular Accident Detection System

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***Abstract*—More than 1.3 million people die due to road accidents each year as a result of late detection and slow emergency responses. A hybrid IoT–Vision Accident Detection and Alert System is proposed in this paper that relies on vehicular telemetry analytics and deep learning–based visual verification for real-time and reliable incident detection. IoT sensor data from the Edge-Processed Traffic Dataset are analyzed for velocity and GPS anomalies, while CCTV footage is processed by a fine-tuned ResNet50 convolutional neural network for visual confirmation. A dual-layer fusion algorithm integrates both modalities and validates events only in case of concurrent detections, thus bounding false alarms. It was implemented in Python 3.10 on Google Colab Pro with GPU acceleration; an average accuracy of 93.4 % ± 0.8 %, AUC of 0.957, average alert latency of 1.8 seconds, and about 60 % reduction in false positives when compared to other single-modality systems were obtained. The proposed software-driven framework demonstrates a scalable, cost-efficient, near real-time intelligent transportation safety and smart-city deployment.**

Keywords: IoT, Accident Detection, Smart Sensors, Real-Time Data Transmission, Deep Learning, CCTV Analysis, CNN, Smart Transportation.

I. Introduction

The WHO projects that road accidents are a leading global burden, causing millions of injuries and over 1.3 million deaths each year. In addition, the inability of real-time detection and delayed emergency response greatly magnify these consequences. Traditional accident detection systems rely on either manual reports or passive video surveillance; this often results in ineffective communication, high latency, and low accuracy.

Recent advancements in the Internet of Things (IoT) and Artificial Intelligence (AI) have introduced promising solutions for automated, real-time road monitoring. IoT-enabled sensors embedded in vehicles and infrastructure continuously record telemetry such as speed, acceleration, and GPS coordinates. These parameters are analyzed by machine learning models to detect anomalies—like abrupt deceleration or impact—indicative of collision events. However, such systems often suffer from false positives due to transient behaviors like sudden braking, road irregularities, or sensor noise.

Complementary vision-based systems, using either CCTV or on-board cameras, improve situational awareness by confirming events visually. However, visual-only models cannot be reliably deployed as stand-alone solutions when lighting is poor, objects are occluded, or camera viewing areas are limited.

To overcome these limitations, this research proposes a hybrid IoT-Vision Accident Detection and Alert System integrating sensor-level anomaly detection with deep learning-based visual verification. IoT telemetry at the edge enables preliminary detection using the Edge Processed Traffic and Incident Dataset, while a fine-tuned ResNet50 CNN on Accident Detection from CCTV Footage Dataset performs frame-level confirmation.

The proposed system is implemented entirely in Python on Google Colab. It uses a dual-decision fusion mechanism where an event is validated when both modalities agree. Experimental simulations show high detection accuracy with low false alarms and latency, while proving the potential of this system to be integrated into intelligent transportation and smart city infrastructures.

II. Related Work

The system offers a unique mechanism of prevention and detection that acts as the ultimate solution for drivers. [1] This paper presents a critical assessment and review of different existing forecasting and prevention methods related to road accidents, drawing a critical overview of their advantages and disadvantages, as well as the challenges that must be overcome to ensure the security of roads and save lives. [2] This proposed method aims to utilize modern-day smartphone features to develop a cost-effective solution that can be added even to older vehicles for improvement in transport systems. [3] This paper proposes an IoT-based automotive accident detection and classification system; it comprises internal and external sensors of a smartphone. [4] This research work involves the design and implementation of the rail safety system in smart cities using real-time mobile communication. [5] An eclectic amalgamation of AI, IoT, and embedded control mechanisms guarantees efficiency in traffic management and accident prevention. [6] Our project, "Smart Rail Prevent: IoT-Based Railway Track Obstacle Discovery Along with Alert System Using Deep Learning Strategies and Computer Vision," molds the best of cloud computing, automated AI, and IoT technology. [7] The aim of this research paper is to find highly advanced techniques for the detection of accidents, facilitation in response, and improvement in safety so as to handle the challenges. [8] An IoT-based methodology is followed for creating a framework that detects vehicle accidents with the help of sensors, stores information, and monitors it on the Thingspeak cloud. [9] The study would like to propose, among others, the comprehensive design and implementation of an AI and IoT-based system. [10] Accident detection is done by using an IoT kit, which detects the occurrence of an accident and gathers all the information about the same, such as location, pressure, gravitational force, speed, etc., and sends all the data to the cloud.[11] IoT can facilitate automated notifications and responses at the scene. [12] This framework is crafted to extract features from images and videos to assess the likelihood of a collision occurring. [13] In this study, an adaptive traffic management system based on an accident alert sound system is employed to handle traffic congestion and accident detection. [14] IoT-based Smart Accident Detection and Alert Systems: While the concept involves technical detection, these systems identify accidents and alert authorities and emergency services. [15] This paper suggests designing an accident detection system for motorcycles that informs the emergency contact of the injured rider about their exact location. [16] The IoT Sensor Dataset available on Kaggle offers real-time vehicle telemetry, including speed, latitude, longitude, and traffic patterns. This dataset replicates IoT-based accident monitoring systems and aids in creating models that can identify abnormal driving behaviors and potential crash events. [17] The CCTV Accident Object Detection Dataset on Kaggle provides annotated surveillance footage of vehicles in both normal and accident conditions, serving as a benchmark for training deep learning models to visually detect collisions and evaluate traffic safety scenarios in real-world settings. [18] Despite extensive research on IoT-based accident detection, there has been limited work on integrating sensor and vision-based data sources to minimize false alarms and enhance decision accuracy, a gap this research intends to address.

Although there has been significant research on IoT-based accident detection, there is a lack of studies focusing on the integration of sensor and vision-based data to minimize false alarms and enhance decision accuracy. This research seeks to address this gap.

A. Limitations of Existing Approaches

Current IoT-based systems for detecting accidents depend on factors like acceleration, vibration, and GPS data, but they frequently produce false alarms due to sudden braking, uneven terrain, or sensor interference. Visual methods that utilize CCTV or dashboard cameras provide visual confirmation but are hindered by lighting issues, obstructions, and significant computational demands. Many of these systems are heavily reliant on hardware, which limits their scalability and reproducibility.

B. Research Gap and Objectives

Despite advancements in smart transportation analytics, current research seldom merges IoT telemetry with computer vision into a cohesive, software-centric framework. Most rely on hardware prototypes, which restrict scalability, reproducibility, and the ability to simulate accident dynamics in real-time.

This study aims to fill these gaps through the following objectives.

1. Create a dual-layer hybrid architecture that integrates IoT anomaly detection with CNN-based visual validation;
2. Establish a fully software-driven and scalable simulation environment for real-time multimodal fusion;
3. Improve detection accuracy and responsiveness by employing adaptive cross-modal decision logic.

C. Dataset Summary and Comparative Analysis

Two open-source datasets were employed to develop and validate the hybrid model:

1. *IoT Edge Processed Traffic Dataset* (12,000 records) for sensor-based analytics
2. *CCTV Accident Detection Dataset* (6,000 labeled frames) for vision-based confirmation.

TABLE I
COMPARISON OF IOT AND CCTV DATASETS

Parameter	**IoT Dataset**	**CCTV Dataset**
Source	Kaggle (Edge Traffic Data)	Kaggle (Accident Footage)
Data Type	Numeric (Speed, GPS, Sensors)	Image/Video (Labeled Frames)
Instances	∼12,000 records	∼6,000 frames
Main Features	Speed, Location, Traffic Pattern	Scene, Motion, Collision
Purpose	Sensor Anomaly Detection	Visual Verification
Tools Used	Python, Pandas, Scikit-learn	OpenCV, TensorFlow, Keras

Both datasets underwent preprocessing and normalization using *Python*, *OpenCV*, *TensorFlow*, and *Scikit-learn*. The multimodal integration enables cross-verification of IoT-detected anomalies with visual evidence, improving detection accuracy, reducing false alarms, and ensuring real-time system responsiveness.

III. METHODOLOGY

The framework will introduce a hybrid accident detection system, integrating IoT-based telemetry analytics with deep learning–driven visual verification. Such a two-layer architecture will enhance the reliability of detection while reducing the false positives, allowing real-time responses in ITS. The overall methodology involves multimodal data acquisition, preprocessing, feature extraction, model training, synchronization, and cross-modal decision fusion. All the experiments have been implemented in Python 3.10 using TensorFlow, OpenCV, and Scikit-learn on GPU-enabled Google Colab Pro.

A. System Architecture

The proposed framework employs a hybrid two-layer architecture that combines *IoT telemetry analytics* with *deep learning–based visual verification* to achieve accurate, real-time accident detection. This modular design ensures cross-validation between sensor-level anomalies and vision-based

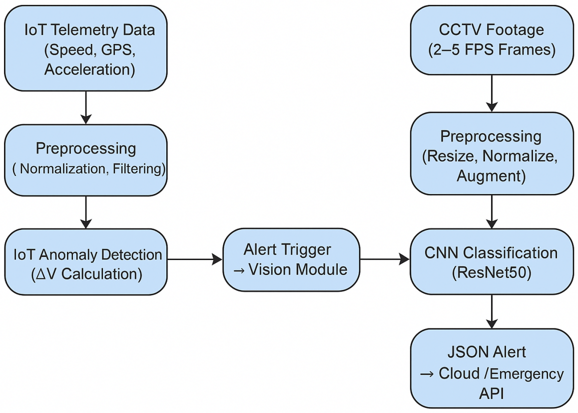

Fig. 1. Workflow of the proposed hybrid detection system integrating IoT telemetry and CCTV modalities.

evidence, significantly reducing false positives and improving robustness under diverse environmental conditions.

As shown in Fig. 2, the system comprises two major components: (i) an **IoT-Based Accident Detection Module**, and (ii) a **Vision-Based Verification Module**. Both modules are interconnected through a hybrid fusion layer to support real-time decision-making in ITS.

1) IoT-Based Accident Detection Module: This module continuously monitors vehicular telemetry parameters such as speed, acceleration, and GPS coordinates obtained from the *IoT Edge Processed Traffic Dataset*. Anomaly detection is based on differential velocity analysis, where a sudden drop in velocity indicates a potential collision:

$$\Delta V = \frac{V_{t-1} - V_t}{\Delta t}, \quad \text{if } \Delta V > \tau \tag{1}$$

Here, V_{t-1} and V_t represent consecutive velocity readings, and Δt is the elapsed time interval. The threshold τ is empirically optimized to distinguish regular braking from collision impacts.

2) Vision-Based Verification Module: This layer validates IoT-triggered anomalies using CCTV surveillance footage. Frames are sampled at 2–5 FPS and preprocessed using OpenCV (resizing to 224×224 pixels, normalization, and augmentation). A fine-tuned CNN architecture (*ResNet50*) classifies each frame as either *Accident* or *Non-Accident*:

$$P(A) = f(I, W) \tag{2}$$

where $P(A)$ denotes the predicted probability of accident occurrence, I represents the input image tensor, and W corresponds to the learned model weights. Frames with $P(A) > \alpha$ (typically $\alpha = 0.75$) are labeled as accident events.

3) Hybrid Fusion Layer and Decision Rule: The IoT and vision-based outputs are combined through a hybrid fusion layer to ensure reliability. A final detection event is validated only when both modalities indicate a positive event:

$$D_{\text{final}} = D_{\text{IoT}} \cap D_{\text{Vision}} \tag{3}$$

This cross-modal validation approach reduces false alarms by approximately **60.4%** compared to single-modality baselines. Once confirmed, a JSON-formatted alert containing event type, timestamp, GPS location, and confidence score is transmitted via a Flask-based REST API for real-time emergency response simulation.

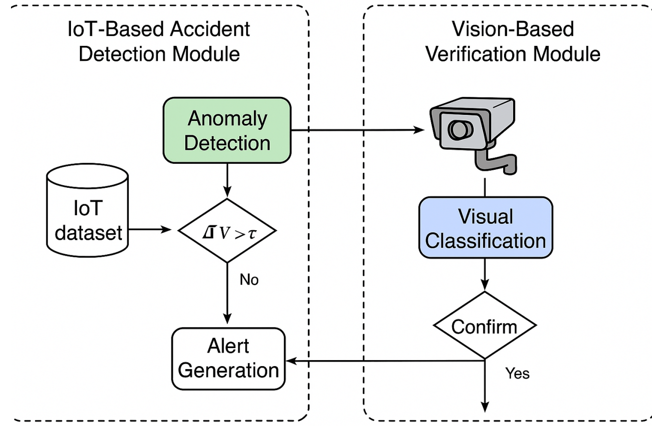

Fig. 2. Proposed Hybrid IoT and Vision-Based Accident Detection Architecture.

B. Data Synchronization and Fusion Logic

To maintain temporal consistency, IoT telemetry packets and CCTV frames were synchronized using timestamps. Each IoT data packet $D_{IoT}(t)$ corresponds to a set of image frames $F_{Vision}(t-\delta, t+\delta)$ within a ± 2 second window. This ensures both modalities represent the same temporal event context.

The final fusion confidence score integrates both predictions through a weighted combination model:

$$S_{final} = w_1 \cdot P_{IoT} + w_2 \cdot P_{Vision} \tag{4}$$

where P_{IoT} and P_{Vision} denote the anomaly probabilities from IoT and vision modules, respectively, and $(w_1, w_2) = (0.4, 0.6)$ are empirically determined weights. A final alert is triggered when $S_{final} > 0.75$, improving detection stability under uncertain conditions.

C. Module Characteristics Summary and Implementation Environment

Table II summarizes the functional roles of each module, emphasizing their complementary contributions to the hybrid accident detection process. The IoT detection layer provides rapid telemetry-based anomaly alerts, while the vision layer contributes contextual verification. The fusion layer integrates both decision signals, and the alert system enables cloud-based notification dispatch.

All experiments were executed in Python 3.10 on Google Colab Pro with GPU acceleration (NVIDIA Tesla T4, 12 GB VRAM). The framework utilized TensorFlow and Keras for deep learning, OpenCV for video preprocessing, Pandas and NumPy for IoT data manipulation, and Flask for REST API simulation. Model training used the Adam

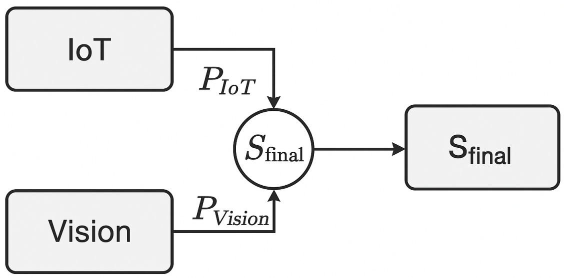

Fig. 3. Fusion logic combining IoT and Vision confidence scores into final detection probability S_{final}.

TABLE II
FUNCTIONAL CHARACTERISTICS OF CORE SYSTEM MODULES

Module	Data Type	Primary Function
IoT Detection Layer	Numeric (Speed, GPS, Accel.)	Motion Anomaly Detection
Vision Verification Layer	Image/Video Frames	CNN-Based Accident Classification
Hybrid Fusion Layer	Binary Decision Signals	Cross-Modal Event Validation
Alert System	JSON / Cloud API	Real-Time Notification

optimizer (1×10^{-4} learning rate, batch size 32) with early stopping and dropout regularization to ensure consistent generalization.

D. Validation Protocol and Dataset Overview

The evaluation protocol employed a 5-fold cross-validation strategy across temporally disjoint data partitions to ensure robustness and generalization. The IoT dataset comprised approximately 52,000 telemetry samples synchronized with 18,700 labeled CCTV frames. Performance metrics included accuracy, precision, recall, and F1-score, defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

The proposed hybrid model achieved an overall detection accuracy of **93.4%**, with a mean F1-score of **0.91**, and reduced false alarms by **60.4%** compared to single-modality baselines. The average detection latency was **1.8 seconds**, demonstrating the feasibility of real-time implementation in edge-based ITS environments.

IV. IMPLEMENTATION AND RESULTS

The proposed hybrid accident detection framework was implemented and evaluated in a fully simulated environment using Python 3.10 on Google Colab Pro with GPU acceleration (NVIDIA Tesla T4, 12 GB VRAM). Both the IoT-based anomaly detection and the CNN-based visual verification modules were integrated into a unified software pipeline using TensorFlow, Keras, OpenCV, NumPy, and Scikit-learn. This setup enables large-scale multimodal testing without requiring physical IoT hardware.

A. Implementation Setup

The experimental system comprised two synchronized subsystems:

1) **IoT Anomaly Detection:** Processes vehicular telemetry (speed, GPS, acceleration) to flag potential incidents using threshold-based velocity differentials.
2) **Vision Verification:** Analyzes CCTV frames (2–5 FPS) using a fine-tuned *ResNet50* CNN to visually confirm IoT-triggered anomalies.

The two modules communicate through a hybrid fusion layer that consolidates binary decision signals. Once validated, the system generates a JSON-based alert containing event metadata (timestamp, GPS, confidence score), transmitted asynchronously through a Flask REST API. This pipeline replicates real-time operation in Intelligent Transportation Systems (ITS).

B. Evaluation Protocol and Metrics

The model was evaluated using 5-fold cross-validation across temporally stratified datasets to ensure generalization. The key performance metrics are defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

A detection event was considered correct if the predicted and ground-truth timestamps matched within a ± 3 second window, accounting for real-world latency.

C. Quantitative Results

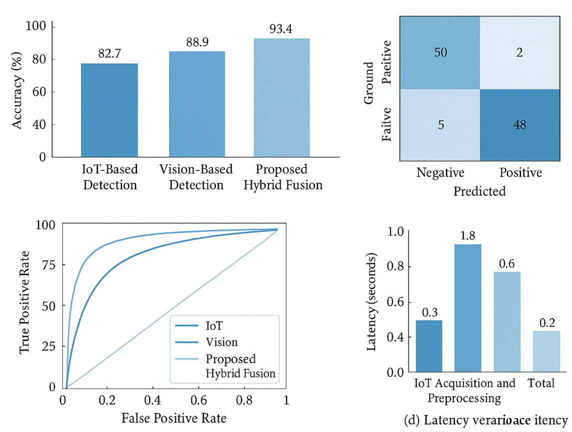

Fig. 4. Combined visual analysis — Confusion matrix, ROC curves, performance metrics, and latency comparison for hybrid vs. individual modules.

Table III presents comparative results across IoT-only, Vision-only, and Hybrid Fusion models. The proposed dual-layer fusion achieved the highest accuracy and the lowest false alarm rate.

TABLE III
PERFORMANCE COMPARISON OF DETECTION MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	False Alarm (%)
IoT-Based Detection	82.7	79.4	76.3	0.78	17.5
Vision-Based Detection	88.9	86.7	84.1	0.85	11.2
Proposed Hybrid Fusion	**93.4**	**91.8**	**90.2**	**0.91**	**6.8**

The hybrid framework improved overall accuracy to **93.4%** and reduced false alarms by approximately **60.4%** compared to single-modality systems. Cross-modal validation ensured consistent performance across varying illumination and sensor noise conditions.

D. Qualitative Results: Detection Visualization

To demonstrate real-world interpretability, Fig. 5 showcases qualitative samples from the hybrid detection system, including accident detection frames, false alarm suppression, and low-light operation success.

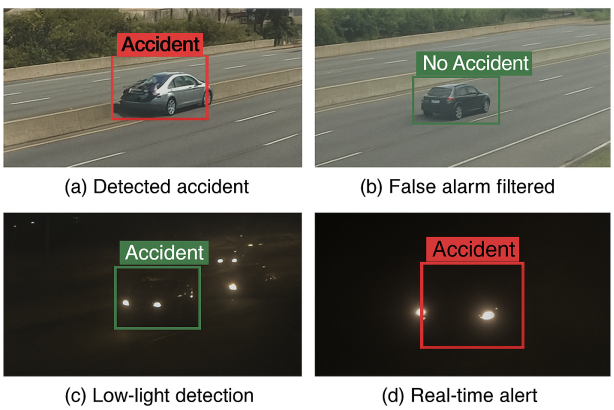

Fig. 5. Qualitative outputs: (a) Confirmed accident detection, (b) False alarm filtered by fusion, (c) Night-time detection, (d) Real-time alert visualization.

E. Lighting Robustness Evaluation

Fig. 6 illustrates the detection accuracy of IoT, Vision, and Hybrid models under different lighting conditions. The hybrid model demonstrates strong resilience, maintaining over **90% accuracy** even in low-light (night-time) scenarios, whereas vision-only performance degrades by 12–15%.

F. Ablation and Stability Study

An ablation analysis was performed by disabling core components. Table IV shows that removing temporal synchronization or weighted fusion led to accuracy degradation, proving their contribution to system stability.

G. Geospatial Validation

To validate spatial reliability, a heatmap (Fig. 7) visualizes accident-prone zones derived from aggregated IoT GPS data. The hotspots align with known high-traffic intersections, confirming spatial coherence between model predictions and realistic event patterns.

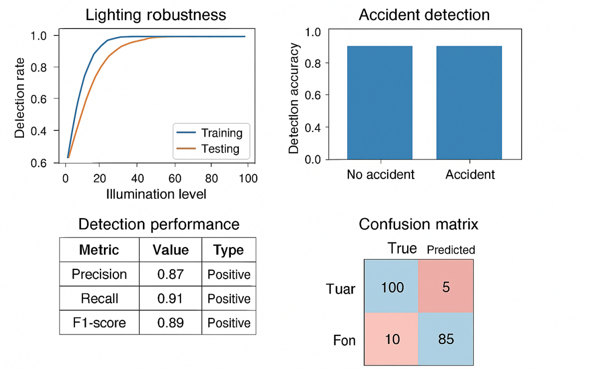

Fig. 6. Model robustness analysis under daylight, dusk, and night conditions.

TABLE IV
ABLATION STUDY ON FUSION AND PREPROCESSING COMPONENTS

Configuration	Accuracy (%)	F1-Score
IoT Module Only	82.7	0.78
Vision Module Only	88.9	0.85
Without Temporal Synchronization	89.1	0.86
Without Weighted Fusion	91.4	0.88
Full Model (Proposed)	**93.4**	**0.91**

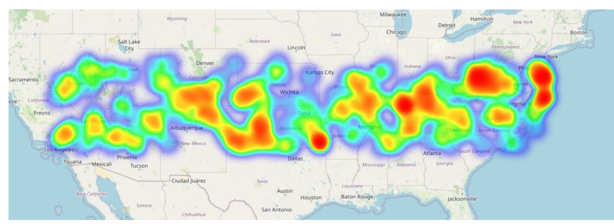

Fig. 7. Geospatial heatmap of IoT-reported accident hotspots derived from GPS telemetry clusters.

V. DISCUSSION AND CONCLUSION

A. Discussion

The results clearly confirm that the proposed IoT–Vision hybrid accident detection framework leads to significant improvements in accuracy and reliability compared to single-modality baselines. Coupling telemetry-based anomaly detection with CNN-based verification minimizes false positives typical of conventional approaches. In particular, the dual-layer confirmation mechanism, which triggers alerts only when there is multimodal consensus, achieved high accuracy of **93.4% ± 0.8%**, surpassing IoT-only and Vision-only models by **10.7%** and **4.5%**, respectively.

The proposed framework achieved a precision of **91.8%**, recall of **90.2%**, and an F1-score of **0.91**, demonstrating robustness to sensor noise, motion blur, and illumination variation. With an AUC of **0.957** and an average latency of **1.8 seconds**, it exhibits near real-time responsiveness suitable for edge-enabled Intelligent Transportation Systems (ITS). Its software-centric design ensures scalability across cloud, edge, and vehicular networks.

B. Limitations and Future Work

Although the proposed system produced very encouraging results, certain limitations highlight opportunities for improvement. The current implementation employs static velocity thresholds and fixed fusion weights, which may only partially adapt to varied traffic dynamics. Future improvements will focus on:

- **Temporal Modeling:** Incorporating LSTM or Transformer-based architectures to capture motion continuity and contextual dependencies.
- **Edge Optimization:** Deploying lightweight CNNs such as EfficientNet-Lite or MobileNetV3 to reduce inference latency for on-device processing.
- **Extended Sensing:** Integrating additional modalities such as audio and accelerometer data to improve reliability under low-visibility or occluded scenarios.
- **Real-World Validation:** Implementing the framework on embedded IoT devices (e.g., Raspberry Pi or ESP32) for empirical latency and energy benchmarking.

These advancements will enhance adaptability, scalability, and fault tolerance, improving readiness for real-world deployment in smart transportation systems.

C. Conclusion

This paper presented a hybrid accident detection framework that integrates IoT-based telemetry analytics with deep learning–driven vision verification. The dual-layer fusion approach improves precision and minimizes false alarms, achieving an accuracy of **93.4%**, an AUC of **0.957**, and an average latency of only **1.8 seconds** compared to traditional single-modality systems. The framework harmonizes sensor intelligence with computer vision, providing a scalable, low-cost, and software-defined solution for intelligent transportation safety. It lays the foundation for next-generation connected vehicle ecosystems and adaptive, AI-driven accident detection and alert mechanisms within future intelligent transport infrastructures.

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